Path Integrated Attenuation Validation

PI: Stephen L. Durden

Jet Propulsion Laboratory, California Institute of Technology, Email: sdurden@jpl.nasa.gov

Overview 1

- This poster highlights three areas of study related to GPM calibration and validation.
- First, we show a few results of comparing Version 4 and Version 5 ocean backscatter and precipitation measurements. (**Panels below**)
- We then focus on non-uniform beam-filling (NUBF). We show that in cases of large NUBF, the estimation of PIA directly from the radar profiles may result in smaller errors. (**Next column**)
- Finally, we show results of a new approach for land surface classification using GPM radar data. The application is for improving the database used for PIA estimation over land. (**Third column**)

2

- For **calibration comparison**, used sigma0 Ku- and Ka-bands over ocean (non-precipitating, corrected for attenuation.
- The table below shows mean values for both months for angles of 0 and 9 degrees.

|	Ku sigma0 Nadir	Ku sigma0 9.3 deg	Ka sigma0 nadir	Ka sigma0 9.3 deg
GPM v4 January	12.2	7.4	11.5	7.8
GPM v5 January	13.7	9.0	11.8	7.8
GPM v4 July	12.4	7.1	11.6	6.6
GPM v5 July	13.9	8.2	12.3	7.2
RADSCAT/SASS2 (5 m/s)	12.1	6.6	-	-
Jason-1 (Tran et al 05)	14.1	-	-	-
Jason-2	13.9	-	-	-
Envisat RA-2	11.3	-	-	-
AltiKa (Quartly 15)	-	-	-	11.2

Ku-band sigma0 increased by 1.1-1.6 dB

Ka-band sigma0 increased by 0-0.7 dB

3

- Plots below are V4 and V5 ocean sigma0 at Ku and Ka-bands versus incidence angle, showing increase in sigma0 in V5

4
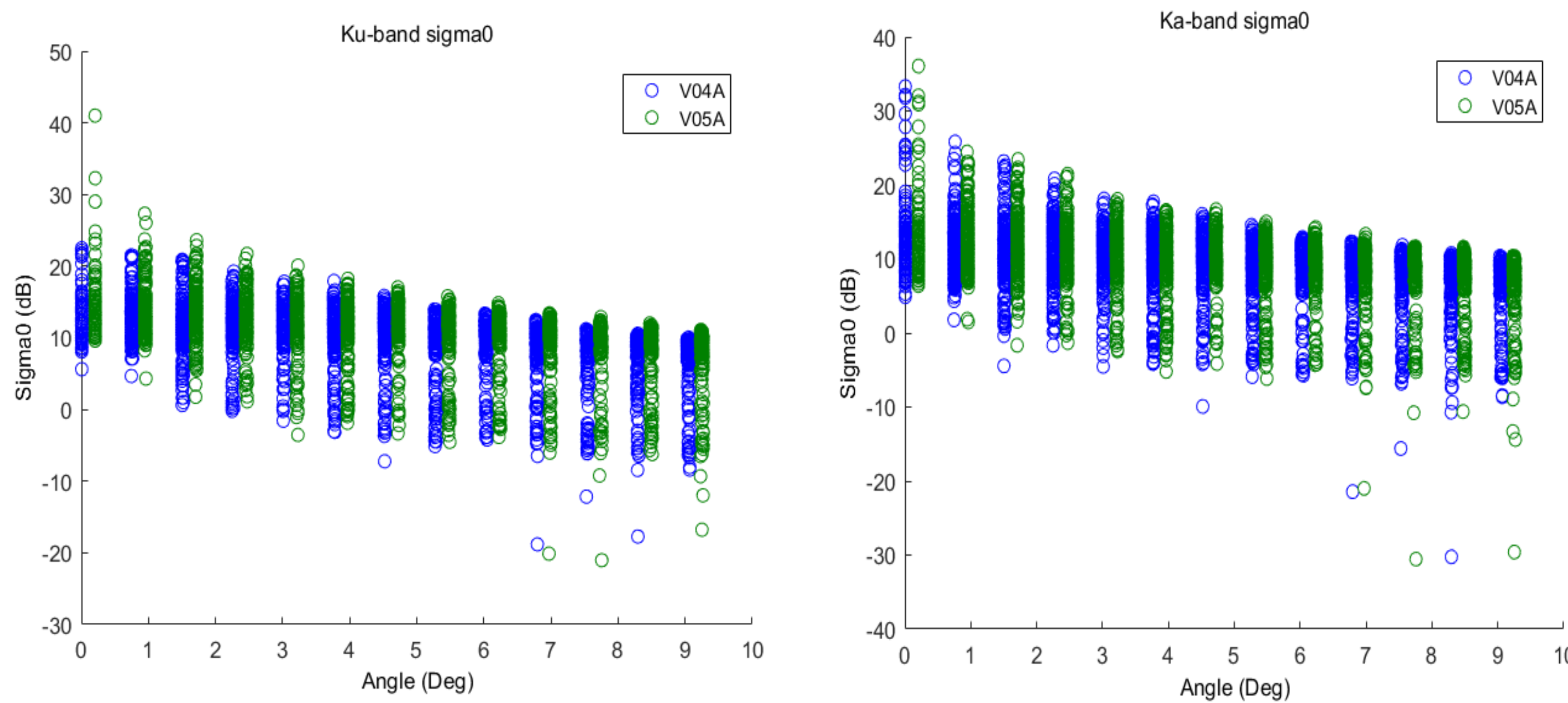
- To check relative calibration between Ku- and Ka-band we examined light precipitation (<22 dBZ) at top of profiles
- For very small particles, expect that Ku- and Ka-band reflectivity should be nearly equal
- For V5, mean Ku/Ka difference is about 1 dB; this is small increase from 0.7 dB for similar data in V4
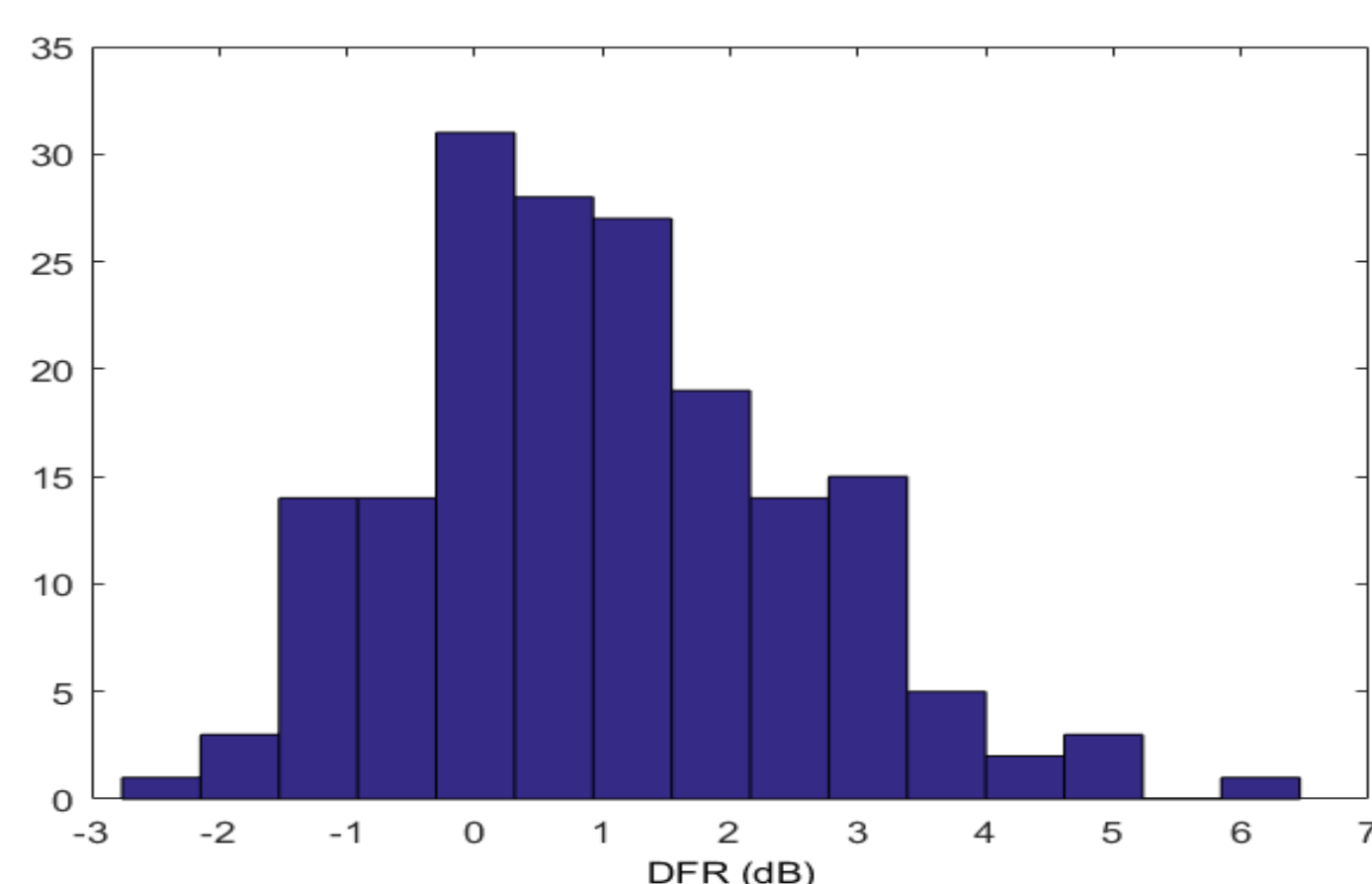
Histogram of DFR (Ku-Ka) in low-reflectivity precipitation

Profile-based Estimation of Path-Integrated Attenuation (PIA) 5

- NUBF is important to understand, detect, and correct since it causes biases in radar estimates
- When there is NUBF, we would like to get the average of the precipitation and the PIA corresponding to this average
- Instead, we measure the average of radar reflectivity and the average of surface backscatter
- Nonlinear relations between precipitation quantities and radar quantities cause biases when using average radar quantities
- Studies using airborne radar data show that PIA estimated with Surface Reference Technique (SRT) can be impacted by NUBF

6

- Goal: develop profile-only PIA estimate (avoid SRT in NUBF)
- Method for algorithm development:
  - Use GPM profiles and SRT-measured PIA
  - Use HS and MS swath data, look for cases with small NUBF to train algorithm (small variance, normal Ka/Ku PIA ratio)
  - Examine various profile statistics in these cases to get best for estimating Ka-band PIA (examples shown below)


7
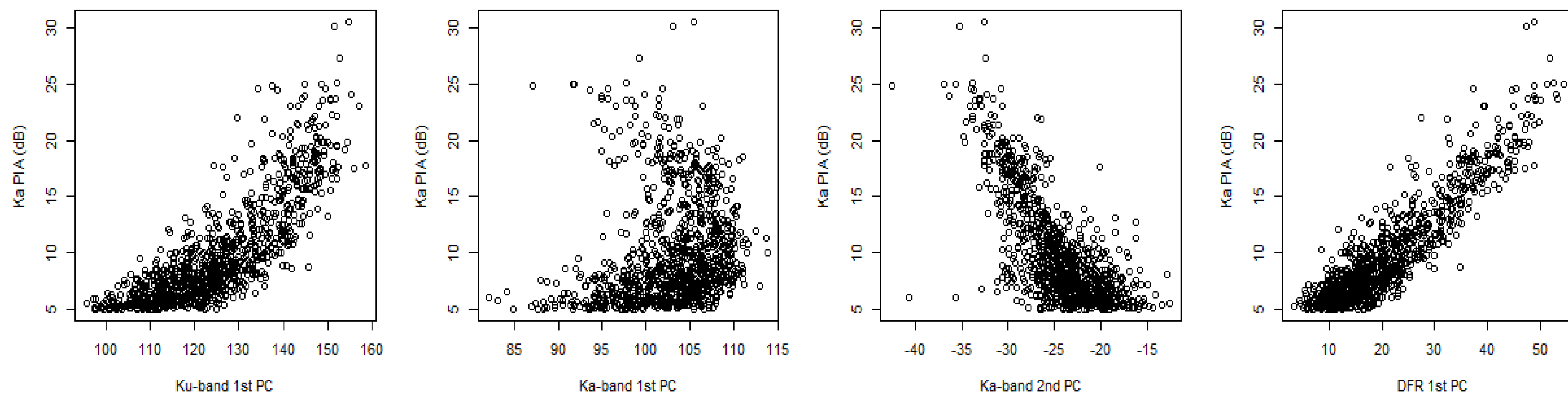
- Best profile statistics for estimating PIA are 1) the dual-frequency ratio (DFR) just above the surface, and 2) the 1st principal component of the DFR profile (Ku minus Ka)
- Used regressions from training data on GPM dataset (2 years); contains varying degree of NUBF
- Histograms show the PIA estimated from reflectivity profiles minus the SRT PIA. Red histogram is for cases with smaller NUBF and blue histogram is for large. Purple is overlap region between histograms.
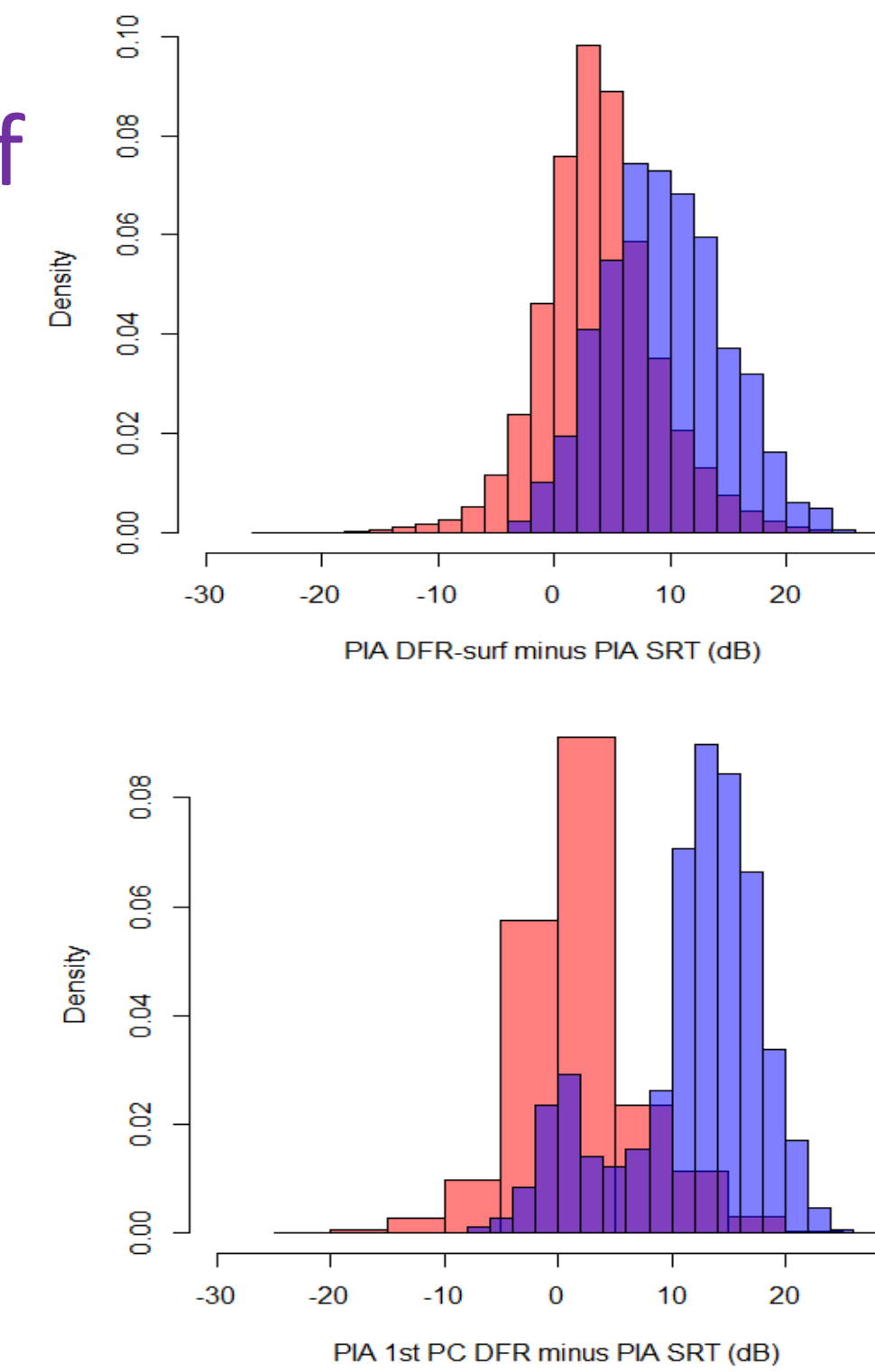
For large NUBF, SRT PIA is typically at least 10 dB smaller than profile-based

8

- Above results suggest that profile-based estimate of PIA may be better than SRT in cases of large NUBF
- Plots below are joint density of the SRT-corrected near-surface reflectivity at Ku-band and the Ka-band reflectivity corrected by SRT and profile methods
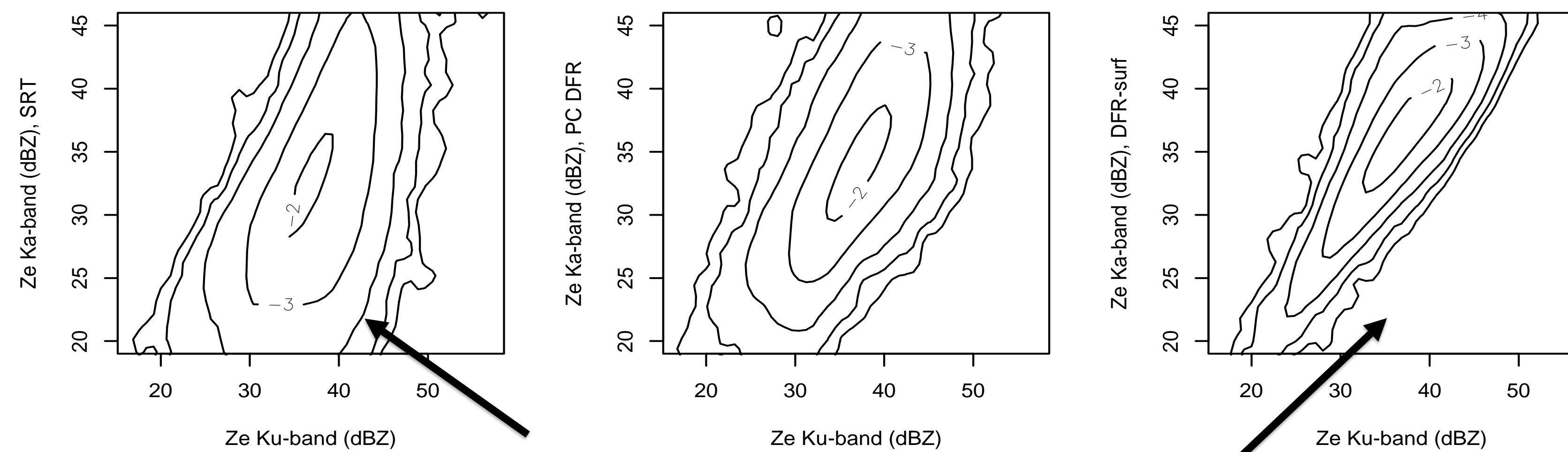

Bias due to severe NUBF, reduced by profile-based PIA

GPM Radar Surface Classification 9

- Several years ago, developed simple k-means based classification of TRMM PR land sigma0 data, with application to SRT over land, Durden et al. (2012)
- Class-based SRT was implemented; maintains multiple references over land, one per land class.
- Provided improvement in some cases but not needed operationally
- Recently, revisited classification with improved method and 3-year GPM record
- Method is based on Bayesian method; prior probability of pixel class is given by Markov Random Field (MRF)

10

- Feature selection
  - Create database with observations binned at desired resolution (e.g., 0.1 degree)
  - Calculate vector at each point that is the mean of the sigma0's at Ku-band versus angle and Ka-band versus angle
  - Calculate principal components and cluster via k-means
  - Assign initial class to each lat/lon bin using k-means results
- Bayesian classification
  - Prior probability is MRF: class probability of pixel is based on classes of surrounding pixels
  - Result: class is determined by distance from observation and distance from surround pixel classes (iterative solution)
  - Effect of MRF is to smooth resulting classification map

11

0.1° lat/lon bins; clustered into 25 classes
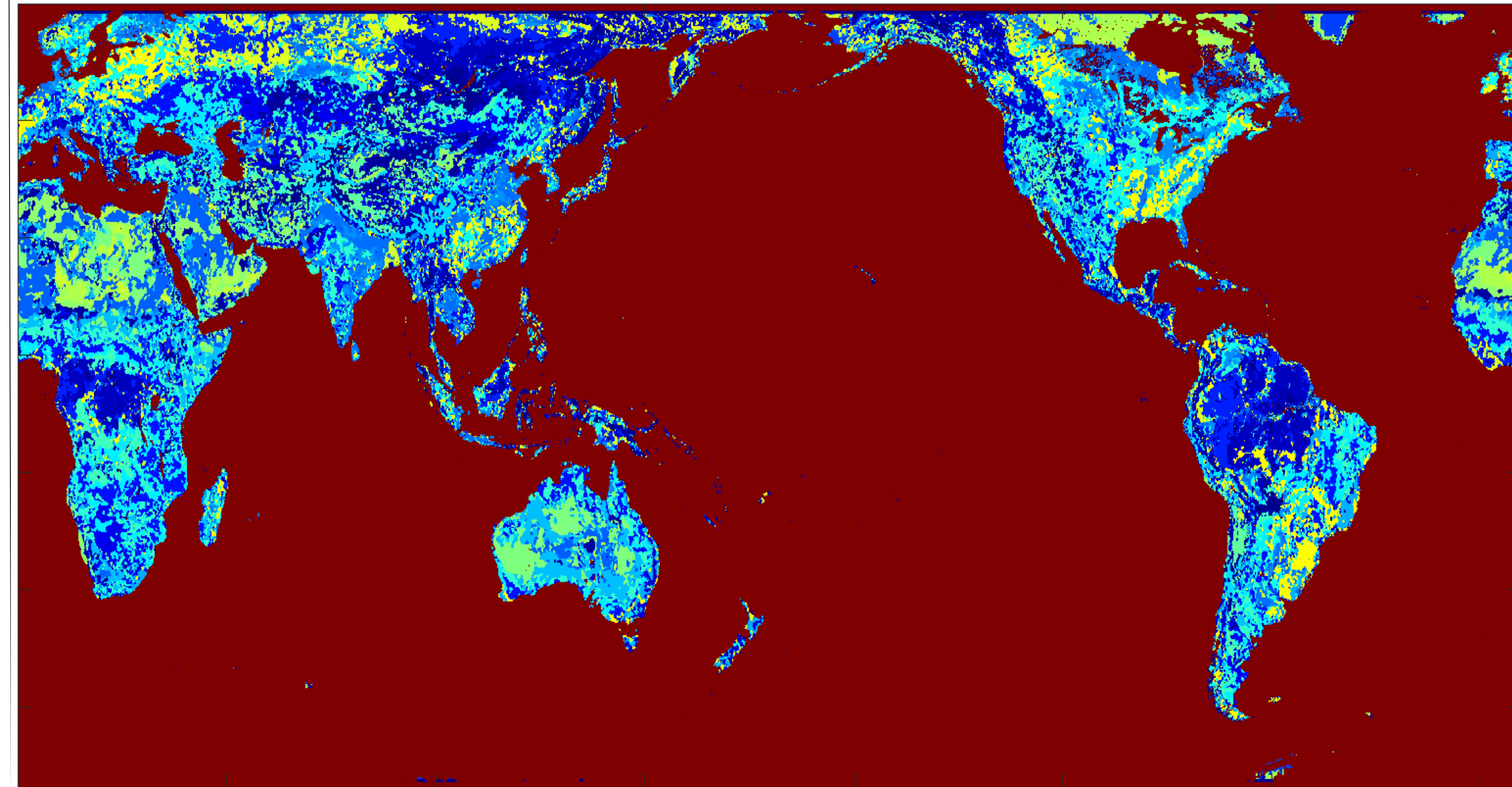
Summary 12

- Absolute backscatter increased in V5, in agreement with expectations; relative backscatter Ku to Ka also increased
- Found that PIA can be estimated directly from the reflectivity profile but with fairly large scatter; SRT should still be used in most cases, but new method has smaller bias in cases of large NUBF
  - Recommendation is use SRT is most cases, use new method when SRT is expected to have large bias; flag and don't use cases with extreme NUBF (S. Tanelli, Trigger Module in development)
- New Bayesian MRF classification approach produces relatively smooth, global surface classification
  - Next step: determine applicability to temporal SRT database generation, e.g., supplementing method of Meneghini and Kim, TGRS (2017)